Evaluate DC Meter Adoption for House-Level Storage Devices

Yang Weng, *Senior Member, IEEE*, Shuman Luo, *Student Member, IEEE*, Qiushi Cui, *Member, IEEE*, Robert Trask, and Hao Wang, *Member, IEEE*

***Abstract*—Although batteries are increasingly adopted in individual households, utilities typically do not know the real behaviors of the customer-owned batteries. Therefore, it is hard for the utilities to evaluate the necessity of adding a DC meter on the DC side of the battery. Meanwhile, the customers do not know the benefits they can get, so they cannot make an adoption decision of DC meters. To solve these practical problems, this paper aims to provide a DC meter evaluation tool for utilities and customers to calculate their costs and revenues. Specifically, we formulate a bi-level optimization framework that considers the battery incentive design and physical law simultaneously. To reflect the reality, the optimization is also based on data-driven constraints based on big utility data and accurate performance. While the optimization problem is complex, we enforce convexity via various designs to provide the optimal solution for incentive planning. Through simulation, the battery incentive design model is tested to be valid under different market rates and case studies. The proposed optimization model provides a promising tool for utilities and customers to evaluate DC meter adoption decisions.**

***Index Terms*—DC meter, data-driven constraint, battery incentive, social benefit, bi-level optimization.**

NOMENCLATURE

Indices

i	Index of user	
t	Index of time slot in the planning horizon	

Parameters

η_i^b	Battery storing efficiency	
η_i^c	Battery charging efficiency	
η_i^d	Battery discharging efficiency	
π_{E}	Unit cost for charging and discharging of the battery	$/W^2$
$\pi_{\mathrm{r,\,t}}$	Electricity retail rate	\$/kWh
$\pi_{\mathrm{w,t}}$	Wholesale electricity price at time t	\$/kWh
$e_i^{\max}$	Maximum power stored in battery	kWh
$e_i^{\min}$	Minimum power stored in battery	kWh
L_i^t	True load of the user i at time t	kWh
N	Total user number	
$p_i^{bd,t}$	Power discharged from battery to meet unmet demand at time t of user i	kW
$p_i^{br,t}$	Power used to charge battery at time t of user i	kW
$p_i^{c_{\max}}$	Maximum charging power	kWh
$p_i^{d_{\max}}$	Maximum discharging power	kWh
$p_i^{gd,t}$	Electricity bought from the grid at time t of user i	kW
$p_i^{gr,t}$	Total power sold to grid at time t of user i	kW
$p_i^{sd,t}$	Power generated by solar panel at time t of user i	kW
T	Total time intervals	

Variables and Functions

$\pi_{\mathrm{c,\,t}}$	Tariff for charging battery	\$/kWh
$\pi_{\mathrm{d,\,t}}$	Tariff for discharging battery	\$/kWh
$\pi_{\mathrm{e,\,t}}$	Rate for selling energy to grid	\$/kWh
$C(p_i^{gd,t}, p_i^{gr,t}, p_i^{br,t}, p_i^{bd,t})$	Total electricity bill for user i	\$
e_i^t	Power stored in battery	kWh

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Yang Weng and Shuman Luo are with the Department of Electrical and Computer Engineering, Arizona State University, Tempe, AZ 85281 USA.

Qiushi Cui is with the State Key Laboratory of Power Equipment & System and New Technology, School of Electrical Engineering, Chongqing University, Chongqing 400044, China (e-mail: qcui@cqu.edu.cn).

Robert Trask is with the Meter Engineering & Testing Services, Salt River Project, Tempe, AZ 85062 USA.

Hao Wang is with the Department of Data Science and Artificial Intelligence, Faculty of Information Technology and Monash Energy Institute, Monash University, Melbourne, VIC 3800, Australia

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I. INTRODUCTION

RECENTLY, the growing penetration of renewable energy sources has revealed that renewables can play a significant role in energy supply, especially in the electricity market [1]. With more photovoltaic (PV) and wind power generators installed in the power grid, it is challenging to balance the electricity demand and the power supply [2], [3]. One of the ideal solutions is the battery, which has become an essential component of the power grid [4]. Batteries can flexibly store and discharge power to balance fluctuations and coordinate power generation and consumption [5]. Mandates and incentives for electricity storage have increased dramatically these days [6]. According to the International Renewable Energy Agency (IRENA), the total stock of electricity storage capacity will grow to $11.89 - 15.72$ TWh if the renewable energy doubles in the energy system by 2030 [7].

Electricity storage can not only participate in frequency regulation, energy arbitrage, or spinning reserves from the grid's side but also play an important role in load shifting and peak shaving from customers' side [8]. References [6], [9], [10] illustrate that energy storage can participate in demand charge reduction. Reference [11] designed an algorithm for battery storage management to help demand-side management. References [12] developed a storage virtualization model to benefit both the aggregator and the customers. Based on the aforementioned facts, electricity storage has attracted more considerable attention nowadays. The producers and the customers will be more involved in exploring the benefits energy storage can bring. However, most of the existing literature, i.e., [13]–[15], used simulated data and make assumptions of the parameters of the batteries to support their ideas, which cannot precisely quantify and monitor the operation of the battery in the real world.

The simulated data of the battery largely depends on the models designed by the toolkit and can not accurately describe complex real-world situations of battery use behavior. For example, [13] only relies on the residential net metering and cannot capture the power exchange between the battery and residential load; while [15] considers self-consumption but has no realistic battery usage data from Sweden to acquire realistic battery behavior. Consequently, to address this issue, it is important for the utilities to have a tool for evaluating DC meter adoption decisions and accurately determining the way of incentivizing customers with batteries.

This motivates us to create a tool for utilities to evaluate the adoption decision of an extra meter at the storage device. The decision is naturally supported by the battery incentive design. There is literature discussing the impact of different incentive schemes on the PV and battery system, like [16]–[18]. Alternatively, in [19], the author emphasized the importance of taking market price and peak charges to determine the size of PV battery systems. However, the value of DC meter adoption is not discussed in those papers. Thus, we focus on the added value of DC meters and include specific incentives to guide the customers' battery usage according to the utilities' needs so that a win-win situation can be guaranteed.

A good battery incentive model considers the physical law and energy arbitrage rules. Many related works create common models to design the tariffs. References [20], [21] design a lower and upper level model barging against each other to optimize both profits. In distributed models, the primary problem is divided into two subproblems consists of the electric companies and consumers. The final objective is to maximize social welfare, i.e., the sum of the benefits of utility and consumers [22]. The game theory model is deployed for optimal time-of-use electricity pricing [23]. Those models reflect reality in some ways but have assumptions when building the models. Those assumptions can be addressed by applying data-driven models to improve the optimization results. As the objective of this paper is to examine the interactions between the utility and the customers under certain incentives provided by the utility, we form a bi-level model to formulate the behavior of each side using data-driven modeling methods.

To solve tariff models, [16] relies on a special solver for the mixed integer linear programming problem, [23] uses backward induction to compute the equilibrium, and [24] applies particle swarm optimization algorithm to find the optimal prices. However, there is no sophisticated design to guarantee the convex shape of the proposed optimization problem. Furthermore, if one follows the traditional optimization method, modeling errors evaluation can be accumulated due to many factors that are not considered [25]. Also, if the data is evaluated statically, overfitting can occur due to the data limitation. After all, we cannot design a method that simply combines the traditional method with simple data analysis, since that may cause bias and even error propagation. Past works ignore the variance of the constraint in the original design [16], [23], [24].

Therefore, we envision a systematical design for utilities' decision-making of DC meters to ensure (1) model generality to avoid overfitting, (2) robustness over limited data volume, and (3) adaptivity for automatic model fixing. The contributions of this paper, thus, include three points:

- A realistic mathematical model for battery incentive design that extracts added value from DC meters to satisfy the physical law. We design a novel model of battery incentive and balance the load demand by considering social benefits that view utilities and customers as a whole.
- We integrate big data processing and physical laws into our optimization method at various operating points of the model. The past work does not have precise modeling on house-level batteries. In this work, the objective function and constraints are data-driven and designed in such a way for precise modeling and easy implementation.
- The modeling accuracy and convergence guarantee are preserved in our designed model. We maintain a good balance between the model accuracy and the requirements of convex functions in the proposed model. Based on this, we conduct a sensitivity analysis for the impact of battery cost on charging/discharging incentives to adjust this model for DC meter adoption evaluation.

Although the problem under study seems a common optimization problem, the highlights of this paper is the battery modeling enabled by the deployment of DC meters. With DC meters, the traditional optimization issue can get rid of unrealistic battery assumptions. The paper outline goes as follows. In Section II, a battery incentive mechanism for battery incentives is formulated. Section III presents the numerical results of this paper, followed by the Conclusions in Section IV.

II. Battery Incentive Design Mechanism Formulation

For the customers that only have AC meters (smart meters installed on the AC side of the AC/DC converter) for net metering, there is a lack of bidirectional information about how much energy is bought from the grid and how much energy is provided by the solar panel and the battery. Also, the bidirectional information about how much energy is used to serve the backup load panel is unclear. However, DC meters provide

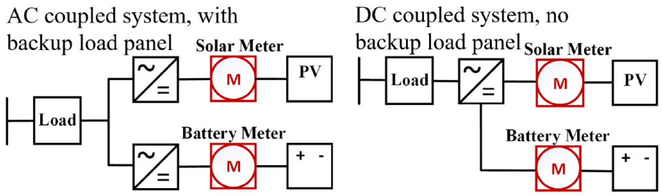

Fig. 1. Future Meter Placement Demonstration. The highlighted red meters are fictitious positions for DC meters.

bidirectional behavior of the battery and directly monitor the battery operation, thus making big data analysis of the battery health condition possible. Fig. 1 gives the recommended future placement of DC meters of our partner utility. The DC meter will be installed by the utility to gain the full observability of the battery operation. The aim of such investment is to discover new business opportunities that involves batteries to encourage the transformation from the traditional power grid to the modern smart grid. We extract some of the typical load profiles from the smart meters that directly measure the battery or measure the battery and solar panel. The billing meter is located before the main load panel which is not drawn in the figure.

The introduction of DC meters enables the novel battery incentive design through precise measurement. The past work did not embed the meter data knowledge into the battery incentive design, therefore, to realize a feasible and solvable data-driven design, we propose a tool for battery incentive design, data-driven constraints, and convex guarantee, as shown in Fig. 2. The proposed method is based on DC meter, data analytics and optimization techniques. Next, we systematically develop a flowchart as shown on the right hand side of Fig. 2. First, prior knowledge about the networks, including topologies, policies, etc., is obtained from utilities. As we know, batteries can benefit homeowners by storing excess generations for later use to reduce electricity bills and provide backup power in case of emergency. Batteries also benefit utilities by relieving the grid from short-term high demand if battery owners are motivated wisely. Based on this knowledge, it is necessary to design a model that considers the benefits of the utilities altogether with the customers, namely the social cost.

Therefore, we build a customer-utility bi-level model as the backbone. The upper level is the utility model, which decides the pricing of electricity and other rewards to incentivize the battery and PV generation. After receiving the incentives and rewards signals, the customer model calculates the energy scheduling strategy that maximizes its own benefits while using the PV and battery. Furthermore, the energy scheduling information is sent to the utility, and then the utility designs reasonable incentives that minimize the social cost. Third, the bi-level model is further polished by adding data-driven constraint modeling inspired by utility data. We analyze the load, solar generation, and battery efficiency behavior to provide a precise model. Lastly, we design the objective function and constraints into a convex shape for solving convenience. The four steps achieve a battery incentive design for social benefits, accurate performance with data-driven constraints, and convex guarantee with real-time sensitivity.

The purchase of DC meters and their calibration should be the responsibility of the utilities. Through the social benefit model, the adoption of DC meters reduces total energy costs for the society, which in turn improves the operation efficiency of the utilities who are mostly not-for-profit. For homeowners who are willing to participate in the DC meter program, they can sign contract with the utility to improve mutual benefits. But, this does not mean the homeowners give their full control of batteries to the utility. The utility monitors the battery usage but does not control the batteries. For those who are not willing to participate the DC meter program, they can choose not to ask the utility to install the DC meter for them. There are three assumptions made in this paper:

- The customers are rational and cooperate with the utility to reduce social costs.
- The battery degradation cost follows a quadratic relationship with the battery usage.
- There are a limited number of customer behavior groups to be modeled into battery incentive models.

In the rest of this section, we first elaborate on the data-driven constraint development, then on the customer and utility model of the proposed pricing mechanism. After that, we merge the two models and provide the solution method.

A. Data-Driven Modeling

The power systems are dynamic, and it is hard for the deterministic optimization formulation to capture the characteristics. Consequently, we design a data-driven modeling approach to precisely quantify the customer and utility model. The data used in this part of the analysis is from our partner utility in Arizona. The data contains the solar meter, battery meter, and billing meter data of about 500 customers. The data starts from May 2018 to October 2019. We remove the badge number of the meters so that anything relevant to the location of a user is eliminated. We also use min-max normalization to scale the data to a number between zero and one to hide the user information while preserving the characteristics of the user behavior. For the rate design in later sections, we refer to our partner's rate plan [26] and generalize it using the scaling method. K-means clustering algorithm is applied to the data after min-max normalization. By using Elbow method, we conclude 3 to 4 different behavior patterns of charging and discharging from the battery of the AC coupled system with a backup load panel. We also extract 3 to 4 different behavior patterns of battery charging and aggregate solar and battery exporting of DC-coupled system with no backup load panel. The preliminary results are shown in Fig. 3. Each line with different colors and line styles in the figure shows one specific using pattern. For Fig. 3 (a), there are 4 patterns, where 7.5% of the customers share pattern 1, 7.5% of the customers share pattern 2, 42.5% of the customers share pattern 3, and 42.5% of the customers share pattern 4. For Fig. 3 (b), there are 3 patterns, where 25% of the customers share pattern 1, 12.5% of the customers share pattern 2, and 62.5% of the customers share pattern 3. For Fig. 3 (c), there are 4 patterns, where 14.0% of the customers share pattern 1, 36.0% of the customers share pattern 2, 14% of the customers share pattern

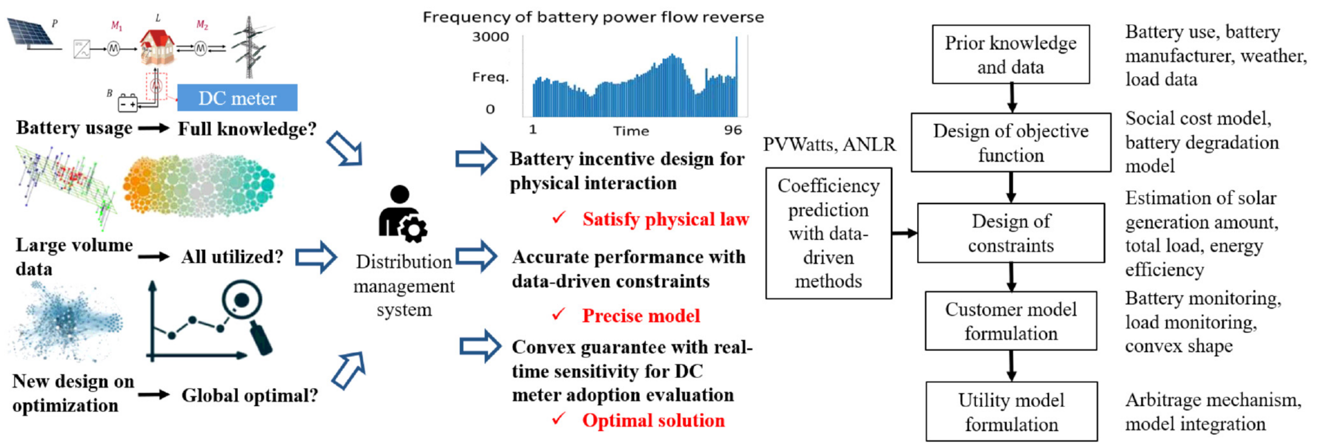

Fig. 2. Overview of the proposed method.

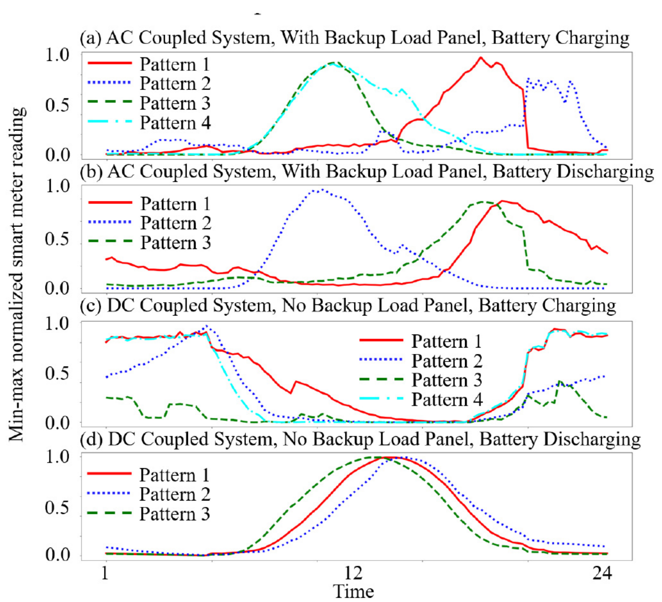

Fig. 3. Raw data and clustered battery meter data patterns. The x-axis is the hours during a whole day. The y-axis is the value of the raw data after min-max normalization.

3, and 36.0% of the customers share pattern 4. For Fig. 3 (d), there are 3 patterns, where 24.0% of the customers share pattern 1, 18.0% of the customers share pattern 2, and 48.0% of the customers share pattern 3.

1) Data-Driven Modeling in the Objective Function: The DC meters enable the accurate modeling of battery usage. To match this advancement, battery degradation needs to be considered. However, battery degradation is sensitive to battery types, battery sizes, manufacturers, and the stage of its life. So, our design considers the charging and discharging cycles that are directly related to the life span of batteries. This means the battery system cost is proportional to $|p_i^{br,t}| + |p_i^{bd,t}|$. The absolute value is not friendly when solving the complicated customer and utility model. Then, we make them quadratic terms to preserve a convex shape [27]. The battery degradation term then becomes proportional to $(p_i^{br,t})^2 + (p_i^{bd,t})^2$. The question is how to choose the battery degradation coefficient. We employ a data-driven method to get the coefficient that has an artificial unit of $\$/W^2$ if we want to match the variables in the degradation term. Users bear the cost of using battery due to degradation denoted as $\frac{\pi_E}{2}((p_i^{br,t})^2 + (p_i^{bd,t})^2)$, in which π_E denotes the coefficient for the quadratic term of charging and discharging. This coefficient will be selected based on the big data collected from battery manufactures. For example, a utility like SRP has information of the registered battery brand of customers, then π_E can be estimated from the battery manual and customer's user behavior. We then estimate the coefficient $\frac{\pi_E}{2}$ using a simple data analytics technique. Concretely, since the unit of the coefficient is artificial – $\$/W^2$, we fit the battery data into a regression model for two reasons: (1) keep the model simple and avoid overfitting with complicated data-driven methods, and (2) preserve the convexity of the objective function for model practicality. Therefore, we build the relationship between the battery degradation cost (y_{Di}) and the battery power usage ($x_{Di} = (p_i^{br,t})^2 + (p_i^{bd,t})^2$): $y_{Di} = \alpha + \frac{\pi_E}{2} x_{Di} + \sigma_i$, where α and $\frac{\pi_E}{2}$ are the y-intercept and the slope of the regression line. To quantify the unobserved values in the battery degradation model, an error term of σ_i is introduced. With n data pairs of x_{Di} and y_{Di}, the slope value of $\frac{\pi_E}{2}$ can be estimated through the ordinary least squares method: $\frac{\pi_E}{2} = (\sum_{i=1}^n x_{Di} y_{Di})/(\sum_{i=1}^n x_{Di}^2)$. This model is justified under multiple battery brands with our utility partners.

It is important to make sure the battery is not charging and discharging at the same time. First, it's common to assume that selling prices are lower than the purchasing prices [28], such that users cannot manipulate buying and selling grid power in the same time slot to make profits. When the user needs more energy, it will have positive net purchase; otherwise, it will have positive net selling. Second, the battery degradation cost and additional penalty term [12] will penalize any unnecessary charge and discharge. For example, charge and discharge at the same time will cancel out a certain amount charge or discharge, resulting in the same net purchasing or selling, but lead to a higher battery degradation cost and penalty, which is not optimal. Therefore, charge and discharge won't happen at the same time due to the additional cost. Also, the quadratic function can lead to a unique solution to the optimal charge and discharge [12].

2) Data-Driven Modeling of Constraints: Since the solar generation amount (denoted as $p_i^{sd,t}$), total load (denoted as L_i^t), energy efficiency (denoted as $\eta_i^b, \eta_i^c, \eta_i^d$) needs accurate prediction to better design the entire model, a data-driven method is utilized to design these constraints. Concretely, we fully consider the physical laws that these parameters need to stand for, including conservation of energy, Ohm's Law, Kirchhoff's Current Law, Kirchhoff's Voltage Law, etc. For example, the power that the grid received from the customer ($p_i^{gr,t}$) is impossible to be larger than the sum of the solar-generated power and the battery output ($p_i^{sd,t}+p_i^{bd,t}$); the total generation should be balanced with the customer load and the battery efficiency has a natural process in time series. Although other papers also uses those laws, we embed those laws into the DC meter enabled battery incentive design framework. To satisfy the three physical constraints, we use a data-driven method to estimate the solar generation behavior, the total load, and the battery efficiency parameters. Specifically, based on the analysis of the characteristic of data, we adopt the adaptive nonlinear local regression (ANLR) method from [29] to conduct the data-driven parameter prediction in our designed constraints.[1] In ANLR, a decision-making procedure is established to select the most suitable algorithm according to the result of the analysis: if the linear degree of the regression model is high, the linear regression algorithm will be selected; if the linear degree is low, quadratic programming will be chosen; if the nonlinearity is obvious, SVM will be implemented. By choosing the most appropriate algorithm according to the linearity of the model, the deviation forecasting model can be solved more precisely and efficiently compared with the direct usage of SVM, in which how to choose the most appropriate kernel function and corresponding parameters is still unsolved.

B. Customer Model

For a residential customer that owns a PV and battery system, a residential customer diagram is shown in Fig. 4. In residential areas where only net metering is available, the detailed power generation and consumption information for the PVs and batteries is unknown. However, with the help of the DC meter and PV meter, the bidirectional power delivery from/to the grid, battery, and PV can be measured. With the additional information, utilities can provide services such as system failing early warnings to prompt customers to check their systems in advance and avoid unexpected interruptions. A display of the readings of solar panels and battery meters can also be added to a user interface, which is a dashboard where customers can log in to view their usage in daily or hourly increments. This can increase the user experience and build a solid foundation to ensure the interactions between the utilities and customers.

[1]The solar generation can be estimated through many algorithms. In this paper, the PVWatts method [30] by NREL is adopted.

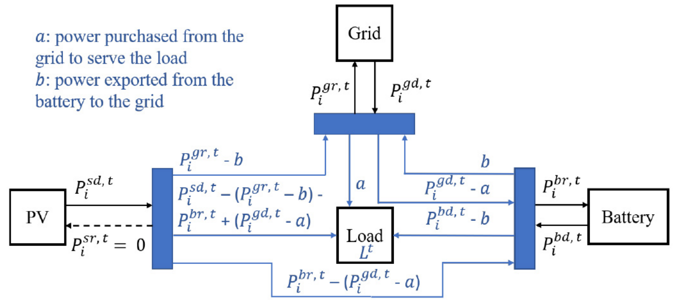

Fig. 4. A residential customer diagram.

Each customer i aims to minimize the daily operating cost by scheduling the local PV power use and battery. The operating cost of user i is defined as

$$C\left(p_i^{gd,t}, p_i^{gr,t}, p_i^{br,t}, p_i^{bd,t}\right) = \sum_{t=1}^{T}\left[\pi_{\mathrm{r,\,t}} p_i^{gd,t} - \pi_{\mathrm{e,\,t}} p_i^{gr,t} - \pi_{\mathrm{c,\,t}} p_i^{br,t} - \pi_{\mathrm{d,\,t}} p_i^{bd,t} + \frac{\pi_E}{2}\left(\left(p_i^{br,t}\right)^2 + \left(p_i^{bd,t}\right)^2\right)\right] + \pi_{\mathrm{p}} \max_{t\in[1,\ T]} p_i^{gd,t}, \quad (1)$$

where $\pi_{\mathrm{c,\,t}} \geq 0$ and $\pi_{\mathrm{d,\,t}} \geq 0$ are rewards set by the utility for incentivizing customers' charging and discharging. We formulate the objective function as

$$\min \quad C\left(p_i^{gd,t}, p_i^{gr,t}, p_i^{br,t}, p_i^{bd,t}\right) + \sum_{t=1}^{T} \frac{\beta}{2}\left(p_i^{gd,t}\right)^2. \quad (2)$$

Note that $\sum_{t=1}^{T} \frac{\beta}{2}(p_i^{gd,t})^2$ is a regularization term that is designed for customers' variables $p_i^{gd,t}$ to address the multiple-solution problem and the regularization term does not change the optimality of customers' cost minimization problem when the coefficient β is set to be small enough.

Equation (1) is a model of a collaborative customer. When this customer is not responding to utility signals, the customer model becomes:

$$C_{non-coll}\left(p_i^{gd,t}, p_i^{gr,t}, p_i^{br,t}, p_i^{bd,t}\right) = \sum_{t=1}^{T}\left[\pi_{\mathrm{r,\,t}} p_i^{gd,t} - \pi_{\mathrm{e,\,t}} p_i^{gr,t} + \frac{\pi_E}{2}\left(\left(p_i^{br,t}\right)^2 + \left(p_i^{bd,t}\right)^2\right)\right] + \pi_{\mathrm{p}} \max_{t\in[1,\ T]} p_i^{gd,t}, \quad (3)$$

If the utility is not able to design a realistic $\pi_{\mathrm{c,\,t}}$ and $\pi_{\mathrm{d,\,t}}$ rate pair for its demand response program due to the lack of DC meters, the non-collaborative customer cannot save its cost in such a way. Through the comparison of these two scenarios, the customer with DC meter is able to gain benefits out of the $\pi_{\mathrm{c,\,t}} p_i^{br,t} + \pi_{\mathrm{d,\,t}} p_i^{bd,t}$ term. It satisfies $\pi_{\mathrm{c,\,t}} p_i^{br,t} + \pi_{\mathrm{d,\,t}} p_i^{bd,t} > 0$, where the utility makes sure $\pi_{\mathrm{c,\,t}} > 0, \pi_{\mathrm{d,\,t}} > 0$. Driven by this, the customers are guaranteed to obtain benefits through the installation of DC meters. Therefore, this model becomes practical and the money can end up in the homeowner's hands through utility's direct and dynamic credit compensation.

C. Utility Model

The utility aims to minimize its cost by providing incentives $\{\pi_{c,t}, \pi_{d,t}\}$ to users to schedule their batteries. Users respond to the incentives by optimally scheduling their energy use, and we denote users' optimal energy scheduling as functions of the incentives, i.e., $p_i^{gd,t}(\pi_{c,t}, \pi_{d,t})$, $p_i^{br,t}(\pi_{c,t}, \pi_{d,t})$, $p_i^{bd,t}(\pi_{c,t}, \pi_{d,t})$. Specifically, the utility's cost consists of two parts: the cost of purchasing power from the wholesale market and the reward provided to users. Over the time horizon, the utility cost is defined as

$$C_U(\pi_{c,t}, \pi_{d,t}) = \sum_{t=1}^{T}\left(\pi_{w,t}\sum_{i=1}^{N} p_i^{gd,t}(\pi_{c,t}, \pi_{d,t})\right) + \sum_{t=1}^{T}\left(\pi_{c,t}\sum_{i=1}^{N} p_i^{br,t}(\pi_{c,t}, \pi_{d,t}) + \pi_{d,t}\sum_{i=1}^{N} p_i^{bd,t}(\pi_{c,t}, \pi_{d,t})\right). \quad (4)$$

The utility also collects revenue from users for selling electricity shown as $R_U(\pi_{c,t}, \pi_{d,t}) = \sum_{i=1}^{N} (\sum_{t=1}^{T} \pi_{r,t} p_i^{gd,t}(\pi_{c,t}, \pi_{d,t}) + \pi_p \max_{t\in[1,\ T]} p_i^{gd,t}(\pi_{c,t}, \pi_{d,t}))$.

The utility's payoff maximization problem is formulated as

$$\begin{aligned} \max\ & R_U(\pi_{c,t}, \pi_{d,t}) - C_U(\pi_{c,t}, \pi_{d,t}) \\ \text{s.t.}\ & 0 \le \pi_{c,t} \le \bar{\pi}_c, 0 \le \pi_{d,t} \le \bar{\pi}_d. \end{aligned} \quad (5)$$

We then update the objective for the utility in the bi-level problem to be social cost directly, which determines the optimal reward strategy $\{\pi_{c,t}, \pi_{d,t}\}$ for users' battery energy management. Note that the rewards $\{\pi_{c,t}, \pi_{d,t}\}$ are both non-negative and bounded.

The utility represents the public interest and thus minimizes the social cost consisting of the utility's costs and users' costs. However, the utility cannot directly control users' energy management in practice. Thus the utility incentivizes the charging and discharging of users through the bi-level optimization problem as follows.

$$\min\ \sum_{t=1}^{T}\left(\pi_{w,t}\sum_{i=1}^{N} p_i^{gd,t} - \pi_{e,t}\sum_{i=1}^{N} p_i^{gr,t}\right) + \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{\pi_E}{2}\left(\left(p_i^{br,t}\right)^2 + \left(p_i^{bd,t}\right)^2\right) + \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{\beta}{2}\left(p_i^{gd,t}\right)^2 \quad (6)$$

subject to

$$p_i^{gd,t} \ge 0, \quad (7a)$$
$$0 \le p_i^{gr,t} \le p_i^{sd,t} + p_i^{bd,t}, \quad (7b)$$
$$0 \le p_i^{bd,t} \le p_i^{d\max}, \quad (7c)$$
$$0 \le p_i^{br,t} \le p_i^{c\max}, \quad (7d)$$
$$e_i^{\min} \le e_i^t \le e_i^{\max}, \quad (7e)$$
$$e_i^t = \eta_i^b e_i^{t-1} + \eta_i^c p_i^{br,t} - p_i^{bd,t}/\eta_i^d, \quad (7f)$$
$$p_i^{gd,t} - p_i^{gr,t} + p_i^{bd,t} - p_i^{br,t} + p_i^{sd,t} = L_i^t, \quad (7g)$$
$$e_i^T = e_i^0, \quad (7h)$$

Variables: $p_i^{gd,t}, p_i^{gr,t}, p_i^{br,t}, p_i^{bd,t}, e_i^t$,

where $\sum_{t=1}^{T} \pi_{w,t}(\sum_{i=1}^{N} p_i^{gd,t})$ is the cost of utility's cost of purchasing power from the wholesale market and $\pi_{w,t}$ is the market price. For consumers, $\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{\pi_E}{2}((p_i^{br,t})^2 + (p_i^{bd,t})^2)$ is the total cost of battery operation.

The developed incentive signals provide more flexible operation of users' batteries to the utility compared to the traditional energy arbitrage pricing design. In traditional energy arbitrage, a time-of-use or dynamic pricing is designed for energy purchase. Then the users schedule their batteries to perform energy arbitrage, i.e., charging at low prices and discharging at high prices, such that energy purchase (recorded in smart meters) leads to the minimum cost. In this work, we study the benefit of installing a third meter for battery storage. In this scenario, the utility has access to more information on users' energy scheduling, including how users consume energy for various appliances and also how users operate their batteries. Therefore, instead of sending one energy purchase signal to users, the utility can send additional incentive signals for users' batteries to better unlock the value of users' batteries in the system operation.

D. Proof of Convex and Solution Method

Based on our careful design, we manage to prove that the proposed optimization problem can be proved to be convex.

Theorem 1. ***The social cost model, including equation (6) and (7) for both the utility and the user is a convex function.***

Proof: First, we show that all constraints in (7) are convex sets. Constraints (7a)-(7e) are all half-spaces, therefore, they are all convex. Constraints (7f)-(7h) are all hyperplane, therefore, they are all convex. Since the intersection of all convex sets is convex, all constraints belong to convex sets. Second, the objective function in (6) is a quadratic function in high-dimensional space, therefore, it is a convex function. In all, the social cost model is a convex function with all constraints belonging to a convex set [31]. The social cost model is convex. ■

To solve the proposed bi-level model, we first search for the optimal charging and discharging incentives using the gradient descent method. The gradient descent direction of this search is to minimize the customer function in Section II-B. When minimizing the customer function, a sequential quadratic programming (SQP) method is used. In this method, the function solves a quadratic programming (QP) subproblem at each iteration. SQP is an iterative procedure which models the nonlinear optimization problems (NLP) for a given iterate $x^k, k \in \mathbb{N}$, by a QP subproblem, solves that QP subproblem, and then uses the solution to construct a new iterate x^{k+1}. This construction is done in such a way that the sequence $(x^k)_{k\in\mathbb{N}}$ converges to a local minimum x^* of the NLP (5), (6a)-(6h) as $k \to \infty$. In this sense, the NLP resembles the Newton and quasi-Newton methods for the numerical solution of nonlinear algebraic systems of equations. It updates an estimate of the Hessian of the Lagrangian at each iteration using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) formula [32], [33]. Next, the results – the power generation and consumption

TABLE I
RETAIL PRICES IN THREE TEST CASES

Time		Case 1: TOU pricing range		Case 2: Super TOU pricing range		Case 3: Flat pricing range	Scaling factor (SF)
Winter season	On-peak	5:00 to 9:00 and 17:00 to 21:00	$0.055 \sim 0.115 \times SF$	15:00 to 18:00	$0.055 \sim 0.115 \times SF$	$0.055 \sim 0.115 \times SF$	$1.2 \sim 1.7$
	Off-peak	Others	$0.055 \sim 0.115 \times 1$	Others	$0.055 \sim 0.115 \times 1$		
Summer season	On-peak	14:00 to 20:00	$0.055 \sim 0.115 \times SF$	15:00 to 18:00	$0.055 \sim 0.115 \times SF$	$0.055 \sim 0.115 \times SF$	$2.7 \sim 4.1$
	Off-peak	Others	$0.055 \sim 0.115 \times 1$	Others	$0.055 \sim 0.115 \times 1$		

Note: For each of the cases, we scale the base retail price between 0.055$/kWh and 0.115$/kWh with a step size of 0.01$/kWh.
When it is winter season, the SF between the on-peak price and the off-peak price is from 1.2 to 1.7 with a step size of 0.1.
When it is summer season, the SF between the on-peak price and the off-peak price is from 2.7 to 4.1 with a step size of 0.2.

information from/to grid and battery – are sent to the utility's social cost model for the gradient descent search.

E. Working Mechanism

Similar to the Day-Ahead Energy Market, the utility can announce the battery incentive rate one day or more days in advance for the customer to follow the rate and design an economic battery use plan. The utility sends rate plan or signals to a Web portal. A homeowner has a customer-defined algorithm that downloads day-ahead utility battery incentive rate everyday and recommends best battery use options for the customers. The customer-defined algorithm can be programmed in the battery management system so that the customers do not need to have rich electricity market knowledge and just need to confirm which price-following plan to choose. This can be done with algorithms in an automatic way without jeopardizing the existing battery use schedule of customers.

To motivate the customers to participate, two ways of compensation can be used. First, even if the utility does not directly control the battery, users' battery schedule can indirectly benefit the system by absorbing excessive solar PV generation and reducing peak load. The utility is happy to provide some compensation as incentives to users, e.g., through financial programs. Second and most importantly, in our work, given battery incentive rates, users respond to it to schedule their batteries to minimize total energy costs.

III. NUMERICAL RESULTS

Numerical results include four parts. The parameter settings to conduct the validation are first shown. To show the effectiveness and reflect the physical law, results are exhibited through the base case and incentive tests of customer model behavior analysis. Next, a comparison is made between data-driven and deterministic constraint design. Last, we present the convex guarantee with real-time sensitivity for DC meter adoption evaluation.

A. Parameter Setting

To validate the proposed model in real scenarios, we design the value for the parameters based on actual utility data to validate the proposed approach. In the overall problem, we divide the parameters into three categories: market rate, battery cost, and customer generation/consumption. In the electricity market parameters, there are three primary parameters: retail price (π_r), solar sell-back price (π_e), and wholesale price (π_w). Table I summarizes the electricity prices from utilities. They represent three rate plans during summer and winter.

Without loss of generality, we have tested the proposed method in various parameter settings. Here, we show a representative group of parameter settings in the case study. We define the designed retail prices as the time-of-use (TOU) pricing, super TOU pricing, and flat pricing. As is shown in the table, the on-peak time for case 1 - TOU pricing of the winter season is from 5:00 AM to 9:00 AM and from 5:00 PM to 9:00 PM. There is no peak time for flat pricing as the price will be the same all the time. For each of the cases, we scale the base price between 0.055$/kWh and 0.115$/kWh with a step size of 0.01$/kWh. When it is winter season, we scale the rate between the on-peak price and the off-peak price between 1.2 and 1.7 with a step size of 0.1. When it is summer season, we scale the rate between the on-peak price and the off-peak price between 2.7 and 4.1 with a step size of 0.2. We design such setups to allow a reasonable variation that considers as many real scenarios as possible.

In addition to the retail price, for customers who export power, any excess energy they generate is credited at a fixed price and subtracted from their bill. To increase the generality of the analysis, we conduct simulations under two different feed-in tariffs. One is 0.0285 $/kWh, which is about one-third of the lowest retail price. The other is 0.068 $/kWh, which is about 80% of the lowest retail price. For the wholesale price, some typical historical public data from our partner utility is employed and shown in [34]. Lastly, the battery cost is important. Most of the customers in the configurations that have isolated battery meters, and solar meters use Tesla Powerwall 2.0. The price per powerwall is $6, 500 and an additional $1, 100 supporting hardware is also required. U.S.$ per warranted kWh: 0.17 [35], [36]. Moreover, we demonstrate typical Arizona customer loads and PV generation scenarios for this paper in the Appendix.

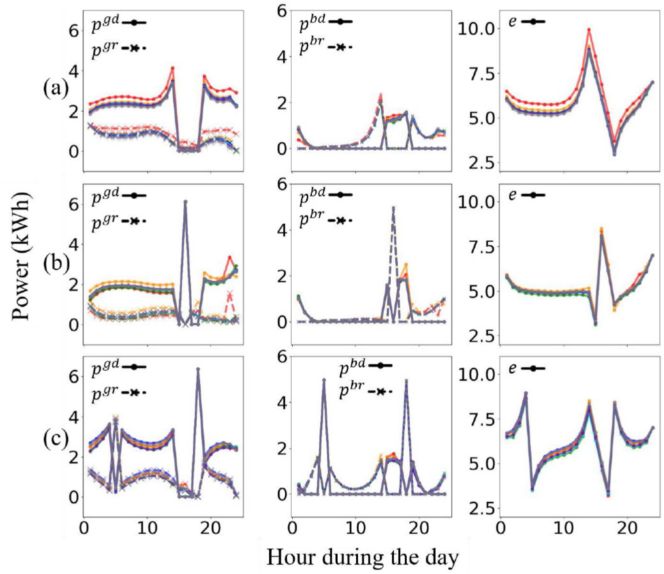

Fig. 5. Results for the customer model. Each line in the figures shows the result of one specific scaling value on top of the base retail price. The left column shows the bi-level consumption information of power delivered from the grid to the customer (p_{gd}) and from the customer to the grid (p_{gr}). The middle column shows the battery discharging (p_{bd}) and battery charging (p_{br}). The right column is the residual energy of the battery (e). (a) the base case customer model performance reflected by residual energy of battery. $\pi_c = 0$ \$ at the time. (b) the incentive case where $\pi_c = 0.4$ \$ when $t = 16$. (c) the incentive case where $\pi_d = 0.4$ \$ when $t = 5$ and $\pi_c = 0.4$ \$ when $t = 18$.

TABLE II
SOCIAL COSTS UNDER FIVE INDIVIDUAL HOUSEHOLD LOADS

Case #	Social cost
1	65.4193
2	130.1974
3	124.0375
4	108.1055
5	112.3598

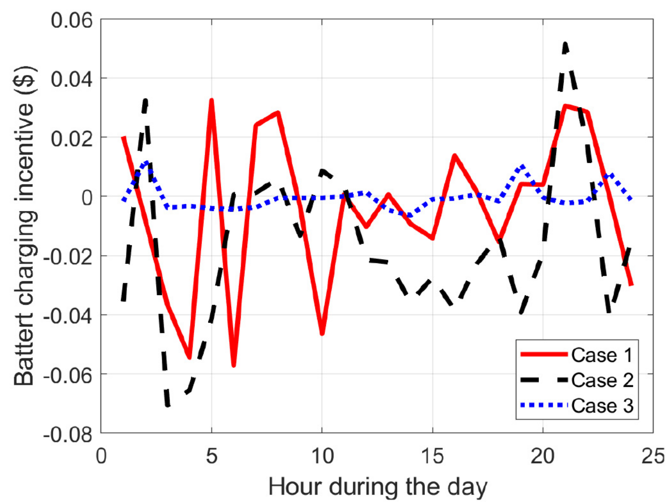

Fig. 6. Battery charging incentives under three test cases.

B. Battery Incentive Design for Social Benefits

1) Base Case of Customer Model Behavior Analysis: The base case exhibits customer behavior without utility incentives. Battery cost π_E is assumed to be negligible, 0.000001 \$/kWh. The customer load is assumed to be a constant number, 1.5 kWh, for testing purposes. Due to the limitation of the space, we show only one case as an example as the other cases follow the same tendency. Fig. 5(a) shows the base case of super TOU pricing in the summer season, where the base retail price is fixed to be 0.085 \$/kWh and the retail price used for simulation is scaled by values in range [2.7, 4.1] with a step size of 0.2. Based on many conducted experiments, we illustrate the performance of the profit-pursuing customer through the measurements of the billing meters, DC meters, and battery residual energy. It is observed through many case studies that the customer purchases less power when the wholesale price is high during peak hours, and the energy source is shifted to the battery.

2) Incentive Tests for Customer Model Behavior Analysis: After introducing the base case, the validity of the customer model is tested. We first provide a single incentive at a certain hour to see whether the customer behavior changes or not. Here, we send a battery charging incentive signal of 0.4 \$/kWh at the sixteenth hour over the base case. From Fig. 5(b), it is observed that the customer purchases from the grid a significant amount of power to charge the battery. By doing this, the customer obtains the profit due to the high charging incentive.

Multiple charging incentives are employed as well to demonstrate the response of the customer model as shown in Fig. 5(c). The customer model exhibits an instantaneous response and is tested to be responsive to the incentive change. We also believe constant loads are okay for algorithm testing. Realistic customer consumption testing is a good way to validate the proposed method. Therefore, five individual household load profiles are added from NREL database [37] for further testing. The simulation results are shown in Table V.

3) Bi-Level Model Behavior Under Different Utility Retail Prices: To illustrate that the battery incentive design satisfies physical laws, we show here the bi-level model's behavior under three comprehensive retail price plans in Fig. 6 according to the parameters in Table I. The off-peak price ranges from 0.055\$/kWh to 0.115\$/kWh with a step size of 0.01. The on-peak price will be scaled by a coefficient ranging from 1.2 to 1.7 with a step size of 0.1 in winter season or 2.7 to 4.1 with a step size of 0.2 in summer season. The information in Table I is based on the rate plan of our partner utility. Different scaling values are designed for reality and generality. The summer season is from May to October and the winter season is from November to April. In Case 3 – the flat pricing plan, the charging incentive is the flattest one among the three curves. In the two TOU-related plans, the utility is continuously sending charging and discharging incentive signals to affect the customer's battery using behaviors. It requires higher incentives for the utility to instruct the customers that participate.

To avoid the negative incentives, the utility and customers could add a constraint to prevent the customers from charging at wrong time. In fact, negative prices occur in both the real-time market and in the day-ahead market [38]. Additionally, it is hard to predict the future and we could view this as an economics game that customers decide to participate or not.

TABLE III
COMPARISON BETWEEN DATA-DRIVEN CONSTRAINTS AND DETERMINISTIC CONSTRAINTS

Objective value deviation	**Deterministic constraints**	**Data-driven constraints**
True parameters	0%	0%
Error in load estimation L	12.51%	0.50%
Error in solar estimation p_{sd}	0.39%	0.97%
Error in efficiency estimation η	75.02%	30.30%

Educated customers eventually will know this and would save more money by using their energy scientifically.

C. Accurate Performance With Data-Driven Constraints

The data-driven constraints provide precise modeling of the battery incentive design problem. To show the advantage of the data-driven constraints, we conduct extensive experiments to test the performance of the data-driven constraints. Here, we demonstrate the results in Table III according to the retail prices of Case 3 in Table I. There are many factors to evaluate model accuracy. Since this paper considers the social cost of the combined utility and customers, we adopt the objective function value in (6). With true parameters, which means the optimization parameters are all real values. The objective function value is calculated at 0.0586. Then, we evaluate the objective function value as the three data-driven parameters change. With deterministic constraints, the constraints are determined based on experience, whose estimation error is assumed to be at least 10% ([29], algorithm M_I). With the ANLR method, we inserted the predicted value (standard error: 4%) into our proposed constraints to get the results for data-driven constraints. The time horizon is 24 hours.

D. Real-Time Sensitivity Analysis for the Impact of Battery Cost on Charging/Discharging Incentives

Battery cost plays a critical role in battery incentive design for customers that own batteries. As the battery technology evolves, its price may diminish. Therefore, our method computes the charging and discharging incentives in real-time as the battery cost goes from 1 $/kWh to 0.001 $/kWh. A relatively broad range is selected to show the robustness and flexibility of the proposed method. Also, the following extreme cases are considered: (1) battery allowance and incentives to households, and (2) the addition of EV as a “free” or cheap battery source in V2G scenarios, if the cost of EV is calculated separately. Therefore, the battery cost may be super low in those scenarios and other scenarios that have not been considered yet. In Fig. 7, we can see that the battery charging is leveraged with the least amount of incentive since the battery cost is so low that the utility does not need to pay at a high rate to cover the battery cost so that the customer changes its power consumption behavior. When the battery cost is comparable with the three market rates, the charging incentive calculation gets complicated. The incentive can oscillate between charging and discharging due to the current market rate environment.

We provide customer costs as a reference for customers' decisions on DC meter adoption under three rate plans. To realize this goal, the proposed customer model in Section II-B

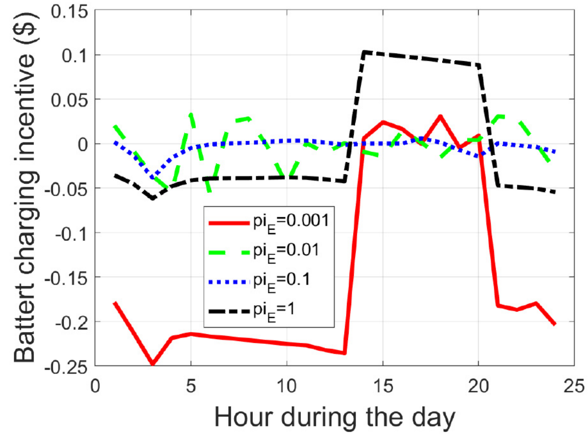

Fig. 7. The impact of battery cost on the battery incentive design. Case 1 retail price is used.

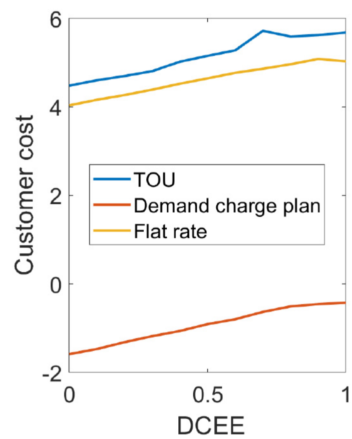

Fig. 8. Customer cost under varying DC meter estimation error.

is adopted. DC meter estimation error (DCEE) is defined as $\mathrm{DCEE}(t) = \frac{|P^{batt}_{real,t} - P^{batt}_{est},t|}{P^{batt}_{real}}$, where $P^{batt}_{real,t}$ is the real battery usage, either charging or discharging, at time t, $P^{batt}_{est,t}$ is the estimated battery usage, either charging or discharging, at time t. It is assumed that 0 DC meter estimation error means DC meters are adopted to provide reliable and accurate battery usage information. Whereas non-zero estimation errors exhibit the quantified estimation inaccuracy. Such an inaccuracy rate exists in cases where DC meters are not installed. As shown in Fig. 8, we show the simulation results under a DCEE range from 0 to 1. In this scenario, the demand charge plan shows the lowest customer cost. However, no matter in which plan, adopting a DC meter indicates the lowest customer cost. In the long run, the error of battery usage estimation increases as the customer costs grow.

E. Strengths and Weaknesses of the Proposed Method

To show the feasibility and strengths of the proposed method, we conduct a cost benefit analysis in Table IV. A baseline without DC meters is created and the battery incentive remains flat at 0.0081$. Also, we assume the estimation error of the battery without DC meter to be 10%. The social costs with and without DC meter and its incentive optimization are

TABLE IV
THE COST BENEFIT ANALYSIS FOR DC METERS

Case #	Social cost without DC meters ($)	Social cost with DC meters ($)	Annual revenue ($)	Return of investment (year)
1	4.4802	4.4804	0.073	1369.84
2	4.6997	4.4804	80.04	1.25
3	4.4802	3.8656	224.33	0.45

TABLE V
SWOT TABLE OF THE PROPOSED METHOD

Strengths	Weaknesses
1. Precise model for battery use behavior. 2. Convex guarantee with real-time sensitivity.	1. Need historical data. 2. Need battery manufacturer information. 3. Need homeowners who are willing to follow utility signals.
Threats	**Opportunities**
1. DC meter information leakage. 2. Bias and variation of the data-driven method.	1. DC meter market. 2. Meter data analytics service.

4.4804$ and 4.6997$. Therefore, after installing DC meters, the social cost saves $4.6997-4.4804 = 0.2193\$/day$. It means the annual revenue is $0.2193 \times 365 = 80.04\$$. If we assume the DC meter costs 100$, it takes $100/80.04 = 1.25$ years to recuperate the DC meter cost. This is a simple case study. This is an encouraging result. If the rate difference at the peak and valley gets larger, the return of investment can be further decreased. To recuperate the DC meter cost, utility and energy policies of such an upgradation play an important role. However, research should not go behind the technology reformation. This paper presents a variety of possibilities once DC meter is adopted for the reference of the utilities and customers.

To comprehensively evaluate the proposed method, we include a SWOT (strengths, weaknesses, opportunities and threats) analysis in this paper. Table V shows the analysis results. The proposed method formulates a realistic mathematical model for battery incentive design that extracts added value from DC meters to satisfy the physical law and balance the load demand by considering the social benefits that view the utility and the customers as a whole. There are three limitations associated with the proposed theory.

- The proposed method requires historical data to determine its parameters. It is not based on old models that rely on experience and fixed parameters.
- The proposed method requires battery manufacturer information to determine parameters like π_E. This is based on past battery usage records or battery factory's testing report and user manual.
- The proposed method requires homeowners who agree with the goal of benefiting society and are willing to follow utility signals.

IV. CONCLUSION

This paper evaluates the value of DC meter adoption by introducing the energy exchange information of the battery. In such a way, we formulate a bi-level battery incentive design by considering the social cost and tying the cost of utility and customer together. We take advantage of the large volume of underutilized data from utility and discover its relevance and fitting rule. The customer model response indicates that the charging and discharging incentives easily drive the customers to alter their power usage whenever needed such as peak shaving. Under different retail prices, we find that it requires higher incentives for the utility to instruct the customers that participate in the TOU-related plan. Furthermore, a cheaper battery cost in the future demands a sophisticated incentive design related to rates and switching between charging and discharging incentives. This paper provides an effective tool for the DC meter adoption evaluation of the utility and customers. Future works can include the following aspects:

- The study on the impact of interaction and coupling of battery usage behavior and household PV systems on incentive rates.
- The demand response study with the existence of DC meters.
- Further work can be done to analyze the customer behaviors for customer portrait.

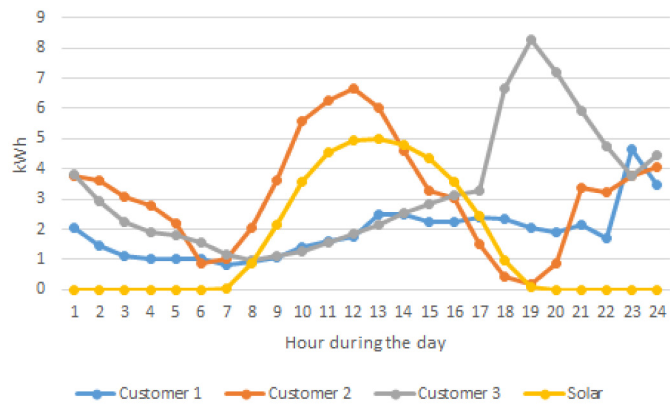

Fig. 9. Customer loads and PV generation scenarios.

APPENDIX
CUSTOMER LOAD AND GENERATION SCENARIOS EXAMPLE

See Figure 9.

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Yang Weng (Senior Member, IEEE) received the B.E. degree in electrical engineering from the Huazhong University of Science and Technology, Wuhan, China, the first M.Sc. degree in statistics from the University of Illinois at Chicago, Chicago, IL, USA, the second M.Sc. degree in machine learning of computer science, and the M.E. and Ph.D. degrees in electrical and computer engineering from Carnegie Mellon University (CMU), Pittsburgh, PA, USA. He joined Stanford University, Stanford, CA, USA, as a TomKat Fellow of Sustainable Energy. He is currently an Assistant Professor of Electrical, Computer, and Energy Engineering with Arizona State University, Tempe, AZ, USA. His research interests include power systems, machine learning, and renewable integration. He was a recipient of the CMU Deans Graduate Fellowship in 2010, the Best Paper Award at the International Conference on Smart Grid Communication (SGC) in 2012, the First Ranking Paper of SGC in 2013, the Best Papers at the Power and Energy Society General Meeting in 2014, the ABB Fellowship in 2014, and the Golden Best Paper Award at the International Conference on Probabilistic Methods Applied to Power Systems in 2016.

Shuman Luo (Student Member, IEEE) received the B.E. degree in electrical engineering from the Huazhong University of Science and Technology, Wuhan, China, in 2017, and the M.S. and Ph.D. degrees in electrical engineering from Arizona State University, Tempe, AZ, USA, in 2019 and 2022, respectively, where she is currently a Postdoctoral Scholar. Her research interests include machine learning, big data analysis, and renewable integration in power systems.

Qiushi Cui (Member, IEEE) received the M.Sc. degree from the Illinois Institute of Technology, and the Ph.D. degree in electric engineering from McGill University. He is currently an Associate Professor with the School of Electrical Engineering, Chongqing University. He was working as a Postdoctoral Researcher with Arizona State University (ASU) and served as the Associate Director of Machine Learning Laboratory for Power Systems, Ira A. Fulton Schools of Engineering, ASU. Prior to joining ASU, he was a Research Engineer with OPAL-RT Technologies Inc. from November 2015 to November 2017. His research interests are in the areas of machine learning and big data applications in power systems, power system protection, smart cities, microgrid, EV integration, and real-time simulation in power engineering. He has won three Best Paper Awards from U.K., China, and USA, all ranking first. He was the Winner of the Chunhui Cup Innovation and Entrepreneurship Competition for Overseas Chinese Scholars in the Energy Sector in 2018. He received the Postdoctoral Research Scholarship from both Natural Sciences and Engineering Research Council of Canada and Québec Research Fund—Nature and Technology (FRQNT) and held the MITACS Accelerate Research Program Fellowship from Canada.

Robert Trask received the B.S. degree in electrical engineering from Northern Arizona University. He works at Salt River Project.

Hao Wang (Member, IEEE) received the Ph.D. degree from The Chinese University of Hong Kong, Hong Kong, in 2016. He was a Postdoctoral Research Fellow with Stanford University and a Washington Research Foundation Innovation Fellow with the University of Washington. He is currently a Lecturer with the Department of Data Science and Artificial Intelligence, Faculty of Information Technology, Monash University, Australia. His research interests are in optimization, machine learning, and data analytics for power and energy systems. More information at https://research.monash.edu/en/persons/hao-wang.